MACHINE LEARNING TECHNIQUE FOR THE PREDICTION OF SHORT-TERM LOAD DEMAND: A CASE STUDY

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ABSTACT: *The purpose of this paper is to present a machine-learning approach for forecasting short-term load demand in Kano. Artificial Neural Network (ANN) and Support Vector Machine (SVM) are applied to develop the model. Three independent variables are selected as inputs, and one output is used to discover the level of relationship among the variables that are independent. This approach can ascertain a more precise prediction of the short-term load demand compared to expensive and rigorous experimental techniques. The correlation coefficient (R), coefficient of determination (R^2), Mean Square Error (MSE), and Root Mean Square Error (RMSE) were used as indicators to evaluate the prediction accuracy of the selected algorithms. ANN gives a close accurate output as follows: R=0.97539, R^2=0.951385, MSE=0.003674 and RMSE=0.060369.*

KEYWORDS: Load demand forecasting, Back Propagation Neural Network (BPNN), Support Vector Machine (SVM).

INTRODUCTION

Presently, electrical energy covers the socio-economic growth of every country. It has an effect on every aspect of human growth, such as transportation, entertainment, education, and healthcare [1]. Inconsistent reliability of electrical power still remains a challenge in many sections of Sub-Saharan Africa as well as for many sections of Nigeria [2]. Solar energy is one among the major types of renewable energy sources in Nigeria. It is the energy that the sun provides for solar applications like solar thermal systems; photovoltaic and solar radiation measurements are essential inputs. For a solar energy conversion system to be designed, it is necessary to understand where and how much solar radiation is available globally [3]. In order to estimate the financial viability and thermal performance of solar energy systems, a precise understanding of the solar radiation statistics for a specific area is a prerequisite [3].

These data may be available in the form of diffuse, direct, and reflected radiation types. These numbers might be required on annual, monthly, or daily basis. Each of these types is crucial and has a distinct purpose in certain applications [4]. Nigeria has good solar resource potentials (the annual average solar radiation varies from 12.6 MJ/m2/day (3.5 Kwhr/m2/day) in the coastal latitudes to about 25.2MJ/m2/day (7 Kwhr/m2/day) in the North [5], but renewable energy technology is still in its infancy. To advance it, a clear plan and timeframe are required. Work needs to be done, in particular, to create the abilities and knowledge required to set up and maintain renewable energy systems [6]. Using different environmental parameters, such as sunshine hours, numerous models have been assembled to predict the amount of global solar radiation on horizontal surfaces. Determining the beam (direct) and diffuse components of the total radiation incident on a horizontal surface is considered crucial by many writers. The short- and long-term performances of tilted flat plate solar collectors, photovoltaic modules, and other devices may therefore be determined after these components are moved over a slanted surface [3].

For instance, Nigeria recorded peak 5375MW from 28 national grid-connected generating plants in the year 2019 for a population of over 190 million people with a peak load demand of 17,700 MW. Nigeria only had a 58% national electricity rate, with a significant discrepancy between metropolitan areas (78%) and rural areas (39%) [5][7]. According to the breakdown of non-electrified clusters at both state and local governments, Kano has a total of 2466 non electrified clusters [5]. The inability to extend the grid to rural areas is mostly caused by inadequate road connectivity, geographic isolation, difficult terrain, dense jungles, low energy demand, high supply costs, low household incomes, and dispersed consumer settling.

Therefore, the majority of rural residents rely on diesel generators to provide electricity. But due to noise pollution, carbon dioxide emissions, the necessity for frequent maintenance, and the resulting high fuel costs, this technique has its drawbacks [8]. In addition, the Nigerian electrical power sector is counseled to rely on renewable energy (RE) sources for energy generation in light of environmental worries about climate change. These renewable energy sources, which include small hydro, biomass, wind, solar, and geothermal, have the advantages of being cost-free, environmentally responsible, and limitless [9]. Machine learning has been to solve the problem in science and engineering owing to it is fast speed and high accuracy [10]–[18]. The fundamental drawback of employing renewable energy sources (RE) to generate power—in particular, wind and solar—is that they are intermittent, necessitating a general oversizing of system components at a large expense [3]. Hence, this research is aimed

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to predict the load demand using two different machines learning viz: artificial neural network (ANN), and support vector machine (SVM) in Kano state, Nigeria.

METHODOLOGY

In this study, a total of 24 hours of data was obtained from the National Meteorological Centre. As a result, 3 input parameters, i.e., hourly wind speed of a year (m/s), hourly global horizontal solar radiation of a year (Wh/m2), and hourly temperature of a year (^oC), are selected due to their influence on the hourly load demand of a year (W). These data sets were normalized between the range of 0 and 1. A Matlab program was developed to estimate the difference between the satellite measured values and the forecasted values. This was determined using the ANN and Support Vector Machine (SVM).

Artificial Neural Network

An artificial neural network (ANN) is a model that borrows concepts from biology and consists of a structure that links input and output parameters [19] through the use of mathematical nodes or neurons that are connected to one another. The three layers of the ANN's structure are organized as an x-y-z structure, with the number of input neurons (x-neurons) being determined by the number of model inputs, the hidden layer (y-neurons), and the output layer (z-neurons), which represents the dependent variable(s) [20]–[22]. The signals are fed into the neuron or node to produce a net input into another neuron, and the weight and bias connected to linkages among the neurons define the number of desired outputs in the output layer [23][24]. Continuous adjustment of these biases and weights applied to each layer will permit the network to be trained. The general equation for an ANN is given in equation (1) below:

$$y_j = \varphi \left(\sum_{k=1}^{m} w_{jk}.x_k + b_j \right) \quad (1)$$

where y_j are the output variables; ϕ is the activation (transfer) function, which indicates the firing rate in the cell and mathematically defines the output from a set of inputs in terms of temporal or spatial frequency. It has the following parameters: x_k are the output variables, w_{jk} are the weight values, m is the number of input neurons, and b_j are the input variables[25].

Figure (1) illustrates the suggested artificial neural network structure (ANN). In this work, the feed-forward back-propagation learning method was used and Leverberg-Marquardt (LM) algorithm was also used for the training, which is the most well-liked, potent, and effective learning process of the ANN structure, as such can be single-layer or multi-layer [20]–[22], [22], [26]–[28]. Information flows only in one route in the feed-forward back propagation neural network (BPNN) as depicted in Figure 1 of the study methodology, i.e., from the input layer to the output layer through the hidden layer. The layers have no effect on one another since they have no feedback loop.

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The trial and error method was used to ascertain the number of neurons in the hidden layer in order to minimize the mean square errors of the models [24]. The transfer function, sometimes referred to as the activation function, usually modifies the target unit's weighted sum of inputs. The tangent sigmoid (tansig) function is used as the activation function (x) in this study and is represented by Equation (2). The hyperbolic tangent (tanh) function and tansig are comparable. They are non-linear differentiable functions with a range of -1 and 1, and are said to be faster than the tanh function. That is why they are more frequently used when speed is a priority [23].

$$\varphi(x) = \frac{2}{1 + e^{-2x}} - 1 \qquad (2)$$

Equation (3) expressed another different type of activation function in ANN which is called Sigmoid (logsig) function. This function is used due to its non-linear differentiable function that is frequently used in the probability forecast, and the outcome of an occurrence has a probability that varies between 0 and 1.

$$\varphi(x) = \frac{1}{1 + e^{-x}} \qquad (3)$$

The most frequent ANN training method uses the Lavenberg-Marquardt algorithm and is known as the multi-layer feed-forward neural network (FFNN) or BPNN[29][30]. Figure (1) illustrates the structure of the BPNN employed in this experiment. The nonlinear functions of the processing elements are added up the received data and generate the outgoing which are transmitted backwards until the necessary target is attained [31]. In this network, all the neurons are connected by terms with variable weights. The fundamental concept behind BPNN is that the weights are updated in order to make the output mean square error as tiny as possible so that the network can learn from the training data [23].

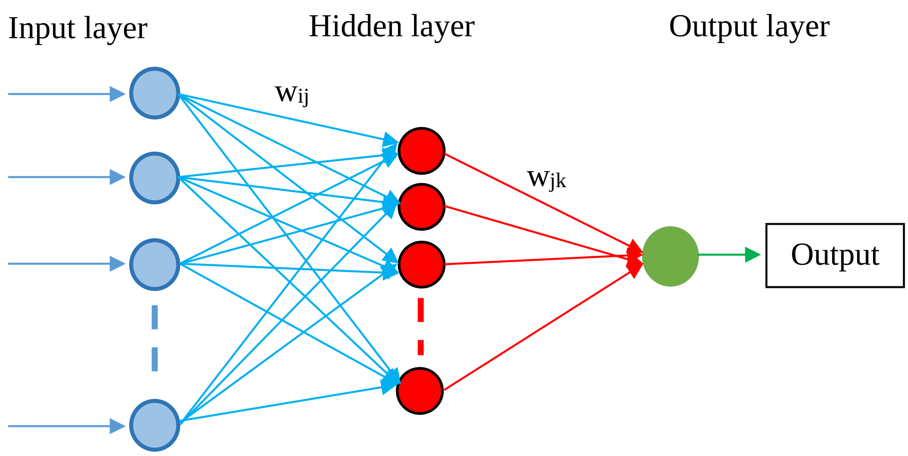

Fig. 1: Architecture of Back Propagation Neural Network

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Support Vector Machine (SVM)

Support Vector Machine (SVM) is an artificial intelligence (AI) model that can successfully solve issues including prediction, classification, regression, and pattern recognition [32]. SVM was first developed by Cortes and Vapnik (1995), and its two key features—statistical learning theory and structural risk minimization—set it apart from previous AI-based models [32][33]. In addition to improving the network's generalization performance, the SVM model can reduce complexity and noise (error) in the structures. As a result, SVM is founded on two fundamental structural layers: the weighted sum of the kernel outputs is the second function, and the first layer is the kernel function weighting on the input parameters [20]–[22], [22], [26]–[28], [34], [35].

Four different techniques are utilized as the kernel function in SVM: linear, sigmoid, polynomial, and Radial Basis Function (RBF). This study used the kernel RBF because of its ability to accurately model complex nonlinear functions. In an SVM model, the data set is close-fitted using linear regression, and then a non-linear kernel transforms the linear outputs using the non-linear data pattern [36]. The calibration data is given as $\{(x_i, d_i)\} \frac{N}{i}$ (x_i is the input vector, d_i is the actual value and N is the sum of the data). The overall SVM function is given as:

$$y = f(x) = w\emptyset\,(x_i) + b \qquad (4)$$

where $\emptyset(x_i)$ indicates feature spaces non-linearly mapped from input vector x [33].

Minimize: $\frac{1}{2}\ \|w\|^2 + C\left(\sum_i^N \quad (\varepsilon_i + \ \varepsilon_i^*)\right)$ (5)

$Subject\ to\colon \{w_i\emptyset(x_i) + b_i - \ d_i\ \le \varepsilon + \ \varepsilon_i^*\ d_i - \ w_i\emptyset(x_i) + b_i \le \ \varepsilon\ \le \varepsilon_i^*\ i = 1,2, \dots \dots, N\ \varepsilon_i, \varepsilon_i^*$ (6)

where $\frac{1}{2}\ \|w\|^2$ is the weights vector norm and C is referred to as the regularized constant. The general conceptual model structure of SVM is illustrated in Fig. 2.

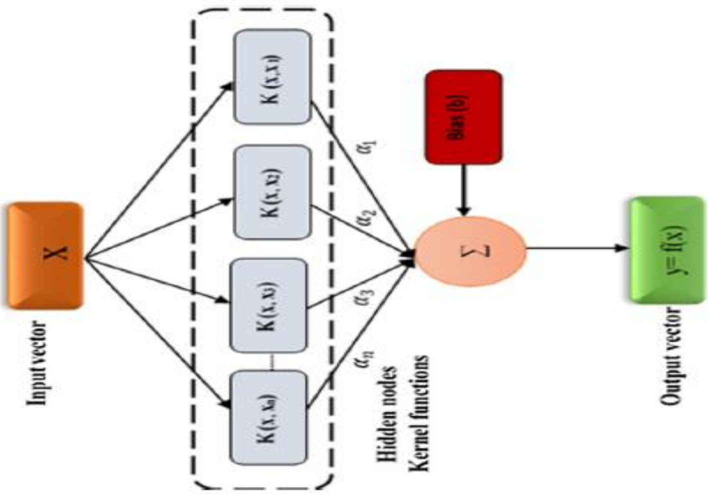

Fig. 2: Architecture of SVM Algorithms [23]

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The problems of dual quadratic optimization can be addressed by alteration process of optimization, in which the parameters of Lagrange multipliers are defined αi and αi*. Vector w in Eq. (12) can be calculated after finding the problem solution of optimization [32].

$$w^* = \sum_{i=1}^{N} \quad (\alpha_i - \alpha_i^*)\, \emptyset(x_i) \qquad (7)$$

Therefore, the overall form of SVM can be in form of Eq. (7).

$$f(x, \alpha_i, w_i^*) = \sum_{i=1}^{N} \quad (\alpha_i - \alpha_i^*)\, K(x, x_i) + b \qquad (8)$$

where k (x_i, x_j) is the kernel function and b is the bias term. The Radial Basis Function (Gaussian) is the most common kernel function and is expressed as: [32].

$$k(x_1, x_2) = exp\,(-\gamma\, \|x_1 - x_2\|^2) \qquad (9)$$

where γ is the kernel parameter.

Assessment of the Models Accuracy

The variables used to evaluate the predictive capability of the technique included Coefficient of determination (R^2), Mean Square Error (MSE), Correlation Coefficient (R), and Root Mean Square Error (RMSE). These assessment indices that are chosen is because they have been successfully used in several research of a similar caliber to demonstrate a prediction model accuracy. The mean squared variation amongst the values anticipated and observed is known as the MSE, and its square root is known as the RMSE.

Normalized MSE and RMSE values are positive, and the lesser they are, the good and more accurate the forecast of the model. The R^2 and R are used to evaluate if a statistical model is appropriate for the provided data. Consequently, they offer statistics on how well a model matches the data, and they range between 0 to 1. The higher the value of R^2 and R, the better the result of the model, and it will signify that the created models have a high degree of precision [37], [38], [38]–[43], [28]. These metrics are theoretically stated in Equations (10) - (13).

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \quad (x_{obsi} - y_{comi})^2}{\sum_{i=1}^{N} \quad (x_{obsi} - \underline{x_{obsi}})^2} \qquad (10)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \quad (x_{obsi} - y_{comi})^2}{N}} \qquad (11)$$

$$MSE = \frac{1}{N}\sum_{I=1}^{N} \quad (x_{obsi} - y_{comi})^2 \qquad (13)$$

where N is the data number, x_{obsi} is the observed data, $\underline{x_{obsi}}$ is the average value of the observed data and y_{comi} are the computed values as such R^2 varies in between -∞ and 1, with a best score of 1.

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RESULTS AND DISCUSSION

In this research, the short-term load demand has been predicted using different AI based models and the results were simulated and evaluated using several performance criteria. It is worth mentioning that modeling the load demand in Kano is essential owing to the rapid population and industrialization growth. Table 1 presents the results obtained during ANN and SVM training. It is apparent from Fig. 3 and Fig. 4 during the training phase that the artificial neural network model performed the best forecasting compared to SVM.

Table 1: Performance Criteria in the Validation Phase

Model	R^2	*R*	MSE	RMSE
ANN	0.9514	0.9754	0.0035	0.0604
SVM	0.8400	0.9165	0.0135	0.1160

Fig. 3 and Fig. 4 display the output time series and bar chart plot of the observed output compared with the ANN and SVM output, which comprise hourly wind speed of the year (m/s), hourly global horizontal solar radiation of the year (Wh/m^2), hourly temperature of the year (^{o}C) and the output hourly load demand of the year (W). According to the training, the model data point is nearest to the outmost grid line of the measured values. Thus, the coefficient of accuracy as calculated was R^2 = 0.9514, R = 0.9754, MSE = 0.0035, and RMSE = 0.0604 respectively. However, these results verified that the model projected an outstanding accuracy for Kano short term load demand.

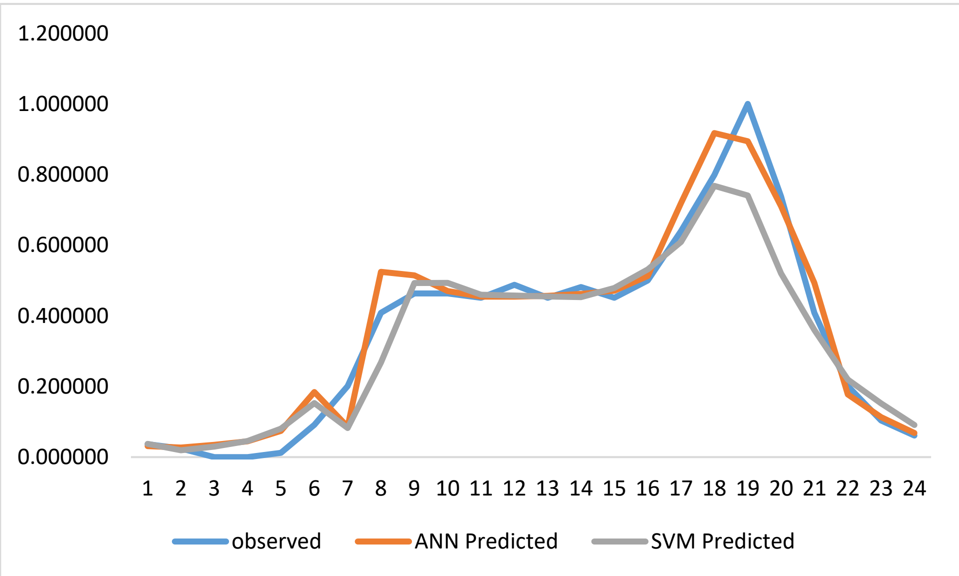

Fig. 3: Time Series Plot

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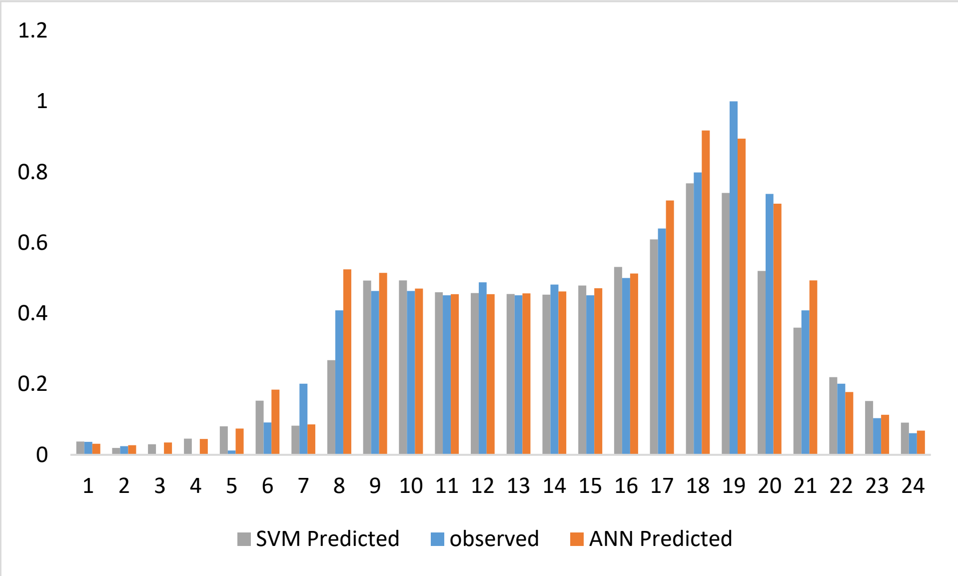

Fig. 4: Bar Chart Plot

CONCLUSION

The objective of this study was to apply machine learning techniques, i.e., Artificial Neural Network model and Support Vector Machine (SVM) for prediction of short term load demand. Results demonstrated that an artificial neural network showed good performance in the training and testing steps. Hence, it can be resolved that the artificial neural network (ANN) is an appropriate model for predicting the short term load demand in Kano. Therefore, itsl recommended that the ANN model should be combined with another soft computing tool or algorithm in order to increase the efficiency performances in the prediction of short term load demand.

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